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A review of combined approaches for prediction of short-term wind speed and power

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ABSTRACT

With the continuous increase of wind power penetration in power systems, the problems caused by the volatile nature of wind speed and its occurrence in the system operations such as scheduling and dispatching have drawn attention of system operators, utilities and researchers towards the state-of-the-art wind speed and power forecasting methods. These methods have the required capability of reducing the influence of the intermittent wind power on system operations as well as of harvesting the wind energy effectively. In this context, combining different methodologies in order to circumvent the challenging model selection and take advantage of the unique strength of plausible models have recently emerged as a promising research area. Therefore, a comprehensive research about the combined models is called on for how these models are constructed and affect the forecasting performance. Aiming to fill the mentioned research gap, this paper outlines the combined forecasting approaches and presents an up-to date annotated bibliography of the wind forecasting literature. Furthermore, the paper also points out the possible further research directions of combined techniques so as to help the researchers in the field develop more effective wind speed and power forecasting methods.

Contents

1. Introduction

Wind energy is of vital importance among the low-carbon energy technologies, which has the potential to achieve sustainable energy supply and constitutes a keystone component for micro-grids in a way towards the smart grid infrastructure. However, stochastic and intermittent wind power generation poses a number of challenges to the large scale penetration of wind power. These wind-related uncertainties can put the system reliability and power quality at risk with the increasing penetration of wind power and thus, the main grid integration issues such as balance management and reserve capacities can come into question [1–3]. Reducing the need for

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balancing energy and making the power generation scheduling and dispatch decisions can be realized with the help of wind speed and power generation forecasts [4,5]. Furthermore, the forecasts can play a pivotal role in keeping the costs competitive by reducing the need for wind curtailments and thereby, increasing revenue in electricity market operations [5]. However, the random and unstable characteristics of the wind make it considerably difficult to forecast the wind speed and power accurately. Hence, extensive efforts have been devoted for the developments and improvements of wind speed and/or power forecasting approaches by numerous energy- and environment-related research centers and universities.

In the literature, many forecasting approaches have been studied and proposed, each utilizing a different technique and performing well with a different prediction horizon. Recent studies in the area of wind prediction are predominantly focused on the short term wind predictions ranging from minutes to a few days due to the importance of these data on power systems. Especially day-ahead predictions are of significant interest for system operations such as scheduling, unit commitment and load following [6,7]. However, it is generally difficult to accomplish such a long-term prediction and moreover, the approaches designed for long prediction horizons may be deficient for shorter terms in terms of prediction performance. Following many studies in the wind forecasting field, it can be indicated that, to date, the targeted performance levels have not been attained with the individual models due to the fact that these models cannot give satisfactory results for all situations. For instance, the physical models produce coarse predictions for short-term horizons while mostly outperform the other models in medium- and long-term horizons. Also, Artificial Intelligent (AI) based models that rely on a large number of historical data for constructing an input/output mapping function can be less effective than some basic conventional statistical methods for certain application areas in the case of inadequate available information. Therefore, the approaches that incorporate the individually superior features of various forecasting models have emerged, called as hybrid models and combined models, in order to obtain an advanced forecasting method for higher accuracy levels and wider forecast horizons.

After evaluating the findings of the studies on the hybrid models, which will be detailed in Section 2, it can be concluded that these models do not generally contribute to the forecasting performance of the individual models considerably and they can even lead to poor performances under some circumstances [8]. On the other hand, combined forecasting methodologies, which follow a different approach and produce the final forecast generally from the weighting of the single approaches, can be a more viable solution for improving the accuracy of the individual models. To that end, the research effort has been recently oriented towards designing new combined algorithms as well as combination methods, which exploit different single prediction models and enhance the prediction performance while providing a reasonable computation time. However, a study on the classifying and summarizing of the combined methods, which might give an insight about the performance, superiority and application area of various algorithms, has not been presented so far. In view of the above requirement, a comprehensive research has been realized making reference to a large number of studies in combination of wind speed and/or power forecasting field in this paper.

This paper is organized in five sections: Section 2 classifies the forecasting methods and presents the fundamental information about the widely preferred methods with relevant example applications from the literature. Section 3 introduces combined models and classifies all the combined-based forecasting studies present in the literature according to the combination procedure adopted. Section 4 is devoted to a general discussion about the most notable findings and the assessment of the future prospects. Finally, conclusive remarks are provided in the last section.

2. Classification and overview of wind forecasting methods

As indicated above, the underlying idea behind combining models can be described as the utilization of the features of different forecasting methods. In this context, it is reasonable to first briefly mention the most widely used forecasting methods in the literature and their characteristics. To this end, the forecasting methods are classified according to the common terminology criteria for wind forecasting methods and inspected by several studies from the literature.

The majority of the wind forecasting techniques can be clustered into two main groups, namely physical methods and statistical methods. In short, the first group takes into account the physical considerations such as local terrain, wind farm layout and temperature to reach the estimate and utilizes the output from Numerical Weather Prediction (NWP) models which provide weather forecasts by using the mathematical model of the atmosphere. The concept of utilizing the NWP models as an input was taken into account by Landberg and then corrections on the wind speed predictions were applied by making use of various programs such as Wind Atlas Analysis and Application Program (WAsP) and PARK [9]. Furthermore, the NWP model output can be used directly for wind speed predictions, as demonstrated in [10]. Likewise, another NWP model, called as Eta Model, was utilized for wind prediction up to 36 h by Lazic et al. and it was shown that Eta model is quite effective in predicting wind energy [11].

The latter aims at describing the relation between historical time series of wind speed (or power) at the location of interest by generally recursive techniques and it can be stated that short term forecasting models are generally based on statistical approaches due to the fact that NWP models require long operation time and large amount of computational resources. Time-varying Autoregressive (AR) model, a well-known and versatile algorithm, developed by Huang and Chalabi [12] for wind speed forecasts can be given as a typical example in the statistical methods. In addition, an Autoregressive Moving Average (ARMA) model, which has a wide range of applications in the literature and defined as a linear function of last known values and last prediction errors, with pre-processing of data, was proposed for longer prediction horizons by Torres et al. [13]. Moreover, Ergin and Shi employed four competing approaches based on the ARMA method for forecasting of wind speed as well as wind direction and strived to determine the best performing model while making comparisons among them according to the Mean Absolute Error (MAE) criterion [14]. Due to the straightforward implementation and relatively low prediction errors for short-term forecasting, Sfetsos built an Autoregressive Integrated Moving Average (ARIMA) model relying again on the classical Box–Jenkins methodology for hourly prediction of wind time series and compared the results obtained with another forecasting methodology [15]. In a similar manner, Kavasseri and Seetharaman investigated the use of a fractional-ARIMA (f-ARIMA) model in order to improve the forecasting accuracy up to 48 h and showed that the developed model outperforms the persistence model, which is the most frequently used benchmark method in the literature and based on the assumption that wind speeds are highly correlated in short terms, especially for longer prediction horizons [16]. Besides, several time series approaches also have been proven effective in wind forecasting. To name a few here, El-Fouly et al. developed a model predicting a certain time interval based on utilizing wind data from the current year and one and/or two previous years for the same interval [6]. Also, Liu et al. investigated the use of another statistical technique, namely Modified Taylor Kriging (MTK) method, for forecasting with the aim of improving prediction performance and obtained a decrement of error in comparison to the ARIMA models [17].

Apart from the mentioned forecasting techniques, Fuzzy Logic (FL) and machine learning algorithms such as Artificial Neural

Networks (ANNs), Support Vector Machines (SVM), Bayesian Networks (BNs) and Genetic Programming (GP) are usually adopted for time series-based wind prediction. ANN, a simplified model of the structure of the neural processing in the brain, has been proven as an efficient forecasting technique due to its capabilities such as self-learning, easy implementation and establishing nonlinear relationships between input and output data sets with a high degree of accuracy. Thus, a large number of recent publications have used ANNs instead of conventional statistical models since they are built on linear assumptions and thereby, deficient in modeling the nonlinearity of the relationship properly. Cadenas and Rivera applied ANN to the hourly wind speed time series and aimed to enhance prediction accuracy developing a model for each month of the year [18]. Then, a comprehensive study was presented by investigating the performances of three different ANN types, namely, Adaptive Linear Element (ADALINE), Feed Forward Back-Propagation (FFBP) and Radial Basis Function (RBF) for 1-h-ahead wind speed predictions and as a result, the authors indicated that different structures and model parameters can yield different forecast accuracies for the same wind data in terms of various evaluation criteria [19]. Another statistical machine learning tool, called as SVM, which is closely related to ANNs and used effectively for nonlinear classification problems, has been recently applied in wind forecasting. Mohandes et al. investigated the performance of the SVM algorithm against that of Multilayer Perceptron (MLP) NNs and proved the effectiveness of SVMs for wind forecasting [20]. Then, Zhou et al. proposed Least Squares SVM (LSSVM), which is a reformulation of the SVM problem in an easier form, for one-step-ahead wind speed forecasting and obtained reasonable accuracy levels compared to the persistence approach thanks to the fine tuning of the parameters [21].

One of the other popular methods investigated for forecasting can be pointed out as FL-based approaches which are preferred particularly due to their ability of modeling system behavior using a set of simple rules. Zhu et al. utilized fuzzy modeling for wind power predictions up to prediction period of two hours while determining the optimal rule numbers by a modified Fuzzy C-Means (FCM) clustering algorithm and tuning the membership function parameters by a BP algorithm [22]. Also, an Adaptive Neuro-Fuzzy Inference System (ANFIS) that merges FL systems with ANNs in order to remedy the lacks of learning ability and of adjusting themselves was successfully utilized in predicting the wind speed and direction for a very short term in Ref. [23]. Besides, Bayesian-based methods carry great potential for the application of wind forecasting and promising results have been obtained, especially in recent studies [24]. A detailed literature survey on applications of BNs on wind energy field including the wind forecasting applications has been very recently presented by Li and Shi [25].

More details about the structure of aforementioned methods as well as that of the approaches not referred to in this section can be found in the comprehensive review studies. These studies provide a survey on the forecasting approaches. Furthermore, these papers examine the peculiarities of the different approaches while utilizing both pairwise and multiple comparisons. In one of the earliest review articles on comparison of several well-known forecasting approaches, especially based on ANNs, was reported by Sfetsos [26]. In the study, the performances as well as estimation times of the models were evaluated for hourly wind speed data and subsequently, it was noted that Neural Logic Network outperforms the other models including ARMA, ANNs and ANFIS. At a more recent date, Costa et al. summarized the widely used short term prediction models following a chronological sequence of publication on the last 30 years of prediction history and pointed out many promising research topics in the same field [27]. In Ref. [28], the wind forecasting models were divided into four main groups, namely, physical models, statistical models, spatial correlation models and other methods such as ANN, SVM and FL. Afterwards, each group was described in detail with the selected examples from the literature. Lastly, several conclusions were drawn comparing the mentioned approaches, as follows: (1) performance of the models can be varied depending on the circumstances, (2) it is often difficult to compare the models accurately due to the different kinds and numbers of input data, and (3) generally speaking, ANN-based models seem to outperform the other models in the sense of providing lower prediction errors. Similarly, Foley et al. published a detailed review on wind power forecasting concerning more up-to-date literature and moreover, presented some results from the previous studies comparing the given prediction errors for different forecast horizons [7].

As can be seen from the mentioned research and review studies, each forecasting model has its own strengths and weaknesses over the other models. In order to gather the present knowledge on the widely used wind forecasting models in the literature, a concise comparison of these basic approaches is given in Table 1.

Besides, a large number of studies can be found in the literature about hybrid and combined prediction approaches which integrate the above mentioned single prediction models in order to provide advanced forecasting models. However, after examining a great deal of studies in this field, it was noticed that the universally accepted definitions for these approaches have not been agreed upon. Therefore, even similar prediction approaches have been named as a hybrid model or a combined model in different papers. Nevertheless, regarding the methodologies adopted in the integration process of the single models in the literature, it can be concluded that hybrid models generally consist of one linear and one nonlinear model, each of which carries out a part of the prediction, i.e. none of the models predict the required future wind speed values as a whole by itself. Hybridizing a linear model along with a nonlinear model to predict the hidden linear and nonlinear components embedded in the original wind speed or power signal, respectively with the aim of improving the prediction performance can be pointed out as a good example for the application of the hybrid approaches [8,29,30].

Apart from the models attempting to predict the linear and nonlinear components of wind speed time series separately before an aggregation process, different hybrid prediction algorithms have been proposed in the literature in order to benefit from the unique capability of single models. In Ref. [31], both a linear model and a nonlinear model were used for predicting the mean monthly wind speed. This hybrid approach resembles the models mentioned in Refs. [8,29,30] in the sense that it utilizes linear and nonlinear models. However, in this approach, the linear model which is based on ARIMA algorithm was not directly applied to the linear component. Instead, a Seasonal ARIMA (SARIMA) and LSSVM model was designed to utilize the effectiveness of the SARIMA algorithm in seasonal time series prediction and that of LSSVM algorithm in nonlinear forecasting in a way that the LSSVM algorithm improves the total accuracy by predicting the residuals from SARIMA prediction. Similarly, Liu et al. put forward two hybrid methods which consist of ARIMA models for deciding the best structure and parameters of the main forecasting models, with the first method being to carry out the predictions with ANN for various time steps and the second being to utilize Kalman filter for the same purpose and data set [32]. Besides, it is worth noting that there exist several algorithms in the literature that are composed of various nonlinear forecasting algorithms, such as a Particle Swarm Optimization (PSO)–ANFIS model [33], and of physical methods such as a GFS–MM5–ANN model [34], a physical technique–ANN model [35] and a NWP–Kalman model [36], and of decomposing and filtering methods such as a Wavelet Transform (WT)–improved time series method [37], a WT–Seasonal

Table 1
Brief comparison of the main methods utilized for forecasting of wind speed and power in the literature.

Wind speed/power forecasting approach	Advantages	Disadvantages
NWP models	Applicable for longer prediction horizons	Weakness in handling smaller scale phenomena, not suitable for short forecast times, requires large computational resource and time
Time series models (AR, ARMA, ARIMA, f-ARIMA, etc.)	Easy to find tools, comparatively basic structure, capability of correcting local trends in data, provides confidence intervals for predictions	Requires a great deal of historic records, difficult to model nonlinear problems and decide the best structure
ANN-based models	Gains knowledge from training data, no need to specify any mathematical model a priori, high data error tolerance, higher adaptability to online measurements	Requires a training procedure and a large number of training data
SVM-based models	High generalization performance	Depends on the tuning of parameters appropriately, complex optimization process and longer training time
Fuzzy logic models	Suitable for systems which are difficult to model exactly, relatively less complex	High complexity and a long process time in the case of many rules
Bayesian networks	Ability to handle missing observations and to avoid the over fitting of data, suitable for small training data sets, suitable for various input data	Requires relatively more effort, depends on the user's expertise level
Kalman filter models	Does not require to store all historic data because of its recursive form	Requires previous knowledge about the system

Adjustment Method (SAM)–RBFNN model [38], a Seasonal Exponential Adjustment (SEA)–BP model [39] and an Empirical Mode Decomposition (EMD)–ANN model [40], named as a hybrid model being distinct from the general classification adopted in the literature and in this paper.

As to combined prediction approaches, which are the main area of interest in this study, the detailed information about the structure and characteristic of the approaches are given in Section 3.

3. Combined wind forecasting methods

As stated earlier, combined forecasting methodologies can improve the final forecasting performance taking advantages of individual forecasting methods which have different performances depending on the data sets, forecast horizons as well as their capability of capturing nonlinearity, and provide great superiorities compared to the individual methods. Among the many superiorities, the potential of utilizing the combined methods in a wider range of application area has a special importance due to the fact that individual models perform well only in a certain situation and therefore different models have to be tested for deciding the most suitable one. The mentioned time consuming drawback of individual methods can be overcome while using combined models, particularly in the case that the determination of the best performing model is complicated.

There is controversy and confusion in the literature about the definition and structure of the combined models. Notwithstanding, it can be indicated that the most widely accepted procedure for combination of models taking place in the literature is to assign a weighting coefficient to each method proportional to their past forecasting performance. Besides, some other approaches are presented as combined models in the literature of wind forecasting by utilizing different methodologies. The mentioned weighting and other combination methods are elucidated and exemplified in detail according to a chronological sequence and by grouping the similar studies, correspondingly in the following sections.

3.1. Weighting-based combined approaches

From a conceptual point of view, the process of weighting used for the combination of the wind forecasting models can be defined as determining the relative effectiveness of each model and providing them an appropriate value that reflects their special importance in the combined model. The general prediction process of these approaches is depicted in Fig. 1.

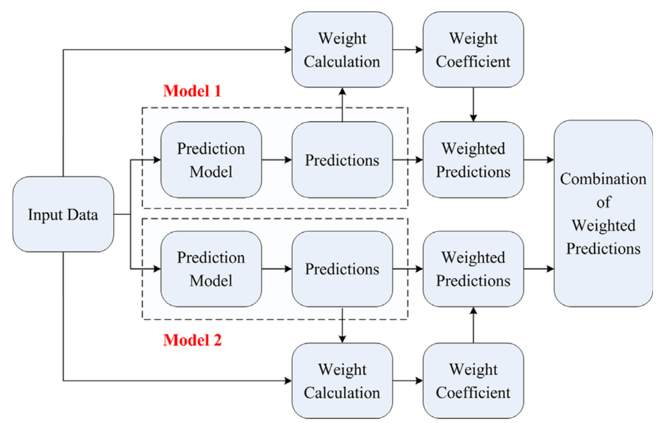

Fig. 1. Flowchart of the weighting-based combined approaches.

With the assumption that the combined model is composed of two single models, the combination of the models is obtained by first predicting the time series with each model simultaneously for a prediction horizon. Then, a weight coefficient is calculated for each model by examining the measured and predicted values. Thus, the coefficients are assigned to the models considering their prediction accuracy and finally, the weighted predictions are merged, as shown in Fig. 1. Herein, the inputs for the models may be the same or different according to the model structures. Nevertheless, it can be noted that the same input data is more preferred for these kind of approaches in the literature. The inputs are mostly composed of lagged wind speed time series; however, other meteorological conditions such as wind direction, temperature, pressure and humidity may make a positive contribution to the accuracy of the prediction model in some cases.

The combined forecast based on a general weighting procedure can be calculated as shown in Eq. (1):

$$\hat{F}_{t+h|t} = \sum_{i=1}^{N} w_i \cdot \hat{f}_{i,t+h|t} \tag{1}$$

where $\hat{F}_{t+h|t}$ is the final forecast for time $t+h$ performed at time t, $\hat{f}_{i,t+h|t}$ is the forecast values of ith model, w_i is the weight corresponding to the ith model and N is the number of models. The formulation of the combined forecast and calculation of the weight coefficients can be realized in various ways and combination models are generally named according to the ways in which

they are determined, for instance, equally-weighted combination model, varied-weighted combination model, regression combination model, discounted mean square forecast error combination model, variance–covariance combination model and so on. In this perspective, Sanchez presented a statistical wind energy forecasting method for up to 48-h-ahead, which combines different time series models regarding the mentioned weighting process and the procedure is implemented in the program SIPREÓLICO, a wind power prediction tool [41]. In this study, the single methods which are to be included in the final model as well as the weight coefficient of the methods which are to be given to each model were time-varying (similar to nonparametric model) with the aim of adapting to the new data obtained from any wind park and determined according to their performance levels. In a more recent study of the same author, a two-step procedure was applied to different data sets for wind energy forecasting, with the first step being applied to two popular covariance-based methods and an Adaptive Exponential Combination (AEC) method in order to combine four individual methods and second step to recombine the obtained forecast combinations for the purpose of evaluating the procedures utilized in the first step and ensuring that the final combination is better than or close to the best combination [42]. Hence, the worst-performing combinations that cause inefficient forecasts were able to be discarded thanks to the mentioned second step and mostly lower error measures were obtained with the final combination compared to the best individual model.

As indicated above, NWP models can also be complemented by the statistical models due to the fact that statistical models tend to perform well generally for predictions up to a few days-ahead and cannot meet the performance requirements for longer prediction horizons. In this context, Ramirez-Rosado et al. proposed two new wind power forecasting approaches for a prediction horizon of 72 h and compared the average Root Mean Square (RMS) errors of these systems [43]. The first proposed system uses a NN Assembling Module (NNAM) for weighted aggregation of the forecasts of an AR module that takes measured power values as input variables and an aggregation module that consists of Power Curve Models (PCMs) that takes forecasted wind speed and direction from a NWP model as input variables. Likewise, the latter system utilized the same inputs; however, it selected the best model that gives the least prediction error values among the combinations of a number of soft-computing-based models such as Kalman filter, ARMA model and various NN models. Compared to the persistence model, it was concluded that the proposed systems increase the prediction performance significantly.

Another combination method which utilizes the maximum entropy principle in order to obtain the weight coefficient of the single models (persistent, ARIMA and four ANN-based models) was put forward and the RMS errors of the method for different prediction times (1–6 h) were compared to those of the regression combination prediction method and of the single methods [44]. The results implied that the combination methods outperform the single models and the proposed maximum information entropy-based model is generally superior to the regression combination model. The concept of entropy was also proposed by Ye et al. for calculating the weighting coefficients of the combination of wind power predictions while integrating several single models such as ARMA model, Elman network model based on the chaos theory, grey NN model and generalized regression NN model [45]. The prediction performance of entropy weight model was proven comparing the MAE values of the hourly power predictions with the single models as well as three combination forecasting models, namely, mean square deviation reciprocal model, binomial coefficient model and vector angle cosine-based model. A more recent combination model based on the maximum entropy principle was given by Han et al. while adopting three NN models with past observations or NWP outputs [46]. As expected, the combined model resulted in better predictions than the single models and a varied-weighted combination model was built for comparison.

Due to the fact that NN models might generate poor predictions for different sites and under different performance metrics, a combination methodology, which is based on Bayesian algorithm and three popular NN models, was designed by Li et al. and the performance of the employed two-step approach was investigated in a comparative manner [47]. In the first step of the approach, the best predictions were selected for each type of NN (ADALINE, BP and RBF) networks regarding the various evaluation criteria. In the second step, the final predictions were carried out via the Bayesian algorithm by weighting the single predictions depending on their posterior model probabilities which are estimated by the Expectation–Maximization (EM) algorithm. The results demonstrated that the proposed approach generally provides reasonable predictions for different conditions while the NN-based single models are only effective in certain cases.

A recent research was developed on the combination of different regression algorithms by means of a so-called Multiple Architecture System (MAS) [48]. Bouzgou and Benoudjit took a data fusion approach, which is an amalgamation process of multiple data, in order to combine the linear and nonlinear regression algorithms by fusion strategies consisting of an averaging operation, a weighted averaging operation and an ANN method. The contributions of the MAS approach were investigated on the basis of a real data set recorded during a period of 10 years while using the basic error metrics. The results reinforced the idea that the linear-based methods are deficient in capturing the stochastic wind speed signal compared to nonlinear ones. Besides, the employed approach possessed more powerful prediction capacity than the single models, especially together with the nonlinear and weighted strategies. Another data fusion approach was put forward by Vaccaro et al. with the same objective mentioned in Ref. [48]; however, in this study, the weight factors were assigned to the measured meteorological data and the values predicted by the atmospheric models instead of the prediction models [49]. The information derived was combined by an adaptive machine learning technique, called as the Lazy Learning (LL) algorithm and the capability of the algorithm was demonstrated for one-day-ahead predictions. At the same year, an interesting approach that combines two decomposition method-based models, namely, WT-ANN and WT-EMD, by weighting the models according to their prediction errors was proposed by Lijie et al. for one-hour-ahead power predictions [50]. Herein, first the performance of the models was compared and it was indicated that the EMD–ANN model is more precise for the adopted prediction time and data set. Then, the predictions were performed with the combined model, in which the EMD–ANN model has a higher weight coefficient because of its performance, and thereby the least normalized error measures were acquired. Similar to the study presented in Ref. [43], De Giorgi et al. investigated the advantages of NWPs in wind power forecasting and nine forecast systems were developed for different horizons ranging from 1 h to 24 h in order to examine the contributions of the NWPs on the forecast accuracy [51]. To that end, firstly an Elman network based only on wind power time series was developed as a benchmark method. Then five forecast systems, having as inputs the wind power time series as well as various outputs from NWP models such as forecasted wind speed, pressure and temperature values, were proposed. In order to improve the forecast performance, two MLP network-based combined approaches including two different ANN submodels were developed and lastly one of the previous systems developed was utilized in an approach which includes wavelet decomposition technique, leading to obtain a new system. In conclusion, among the systems proposed, the best method was

determined as one of the MLP network-based combined systems regarding the Normalized MAE (NMAE) percentage error and frequency distribution of normalized average percentage error. The results obtained from the comparisons with the studies in the literature confirmed the validity of this combined model.

Mahoney et al. proposed a multi-component forecasting system that includes many input data such as weather model data from four National Centers to statistically optimize the weight factors, followed by an energy conversion system and a now-casting system [52]. The weight factors of the individual forecast models were modified for each forecast site and each lead time considering the performances of the models on the previous day. It was indicated that the wind power forecasting system made a major financial contribution to the Xcel energy, an electricity and natural gas company in USA, within the year 2010. Finally, to the best of our knowledge, the last attempt to assess the advantages of weighting-based combined forecasting in wind energy was developed by the authors in Ref. [53]. In this study, the proposed algorithm consists of two models; the EMD–CFNN model which decomposes wind speed series into a certain number of subseries and forecasts each subseries separately before an aggregation process, and the Linear Model which utilizes the measurements recorded in the previous years within the same time period. Subsequently, a weighting coefficient, which is calculated using the Mean Square Error (MSE) pseudo-inverse method, was assigned to each model for a prediction period of 24 h depending on their prior knowledge about the prediction performance in order to blend the mentioned methods. Not surprisingly, the simulations carried out up to one week proved that combined approaches can improve the prediction performance considerably, particularly for longer prediction horizons.

The other approaches denoted as combined models in the literature are classified according to their main structure and briefly explained in Section 3.2.

3.2. Other combined approaches

In the literature, these approaches generally consist of two different models, one for main forecasting task and the other for the auxiliary processes such as data filtering, data decomposition, selection of the best parameter and residual error evaluation. Depending on the function of the models used for the auxiliary processes in the final model, “the other combined approaches” can be gathered into three groups: (1) combined approaches including data pre-processing techniques, (2) combined approaches including parameter selection and optimization techniques, and (3) combined approaches including data post-processing techniques.

3.2.1. Combined approaches including data pre-processing techniques

In the first group, the main objective of the data pre-processing models is, as the name implies, to realize a preliminary process on data sets by decomposing the nonlinear wind speed time series into more stationary and regular subseries which are generally easier to analyze and/or by filtering out the irrelevant and redundant features of the data set. Thus, more stable subseries are obtained as well as the most informative training data is determined enabling to improve the quality of the data and avoiding the unnecessary computation burden. The basic flowchart followed in a large part of the mentioned approaches is illustrated in Fig. 2.

The first model, named as Model 1 in Fig. 2, represents the decomposition model and the other models from Model 2a to Model 2n estimate the wind speed or power values making use of the decomposed time series which is obtained by the means of Model 1. The models used for prediction process of each decomposed series may be the same; however, different models or different structures for the same model are generally adopted in the literature due to the fact that each series has a different frequency and it is, therefore, almost impossible to produce high-accuracy predictions for all series with the same model or structure.

Among the data processing techniques, the WT method can be pointed out as the prevailing approach due to its easy implementation and adaptive ability of time–frequency analysis. The wind data is decomposed by the WT method into low and high frequency components which describe the approximate and detail levels, respectively. The benefits of the wavelet decomposition on the prediction performance have been proven for both linear and nonlinear forecasters taking place in the literature. For a basic time series model, namely AR model, the efficiency of the WT was evaluated for three different prediction times and very high correlation coefficient (R) values were obtained after reconstructing the predictions of the future values of one approximation and three detail levels derived from the transformation of the wind speed data [54]. Similarly, acceptable prediction error margins were achieved for other regression-based models thanks to the WT method. Lei and Ran combined the WT method with ARMA model for one-hour-ahead prediction and showed that the proposed model outperforms the persistence and ARMA models [55]. It is interesting to note that the authors selected the decomposition level as a high value, which is mostly unusual due to the fact that the error values generally increase after a certain level depending on the stochasticity of wind signal. In a subsequent study, DeSheng et al. established an ARMA–ARCH model using a three-level wavelet decomposition and compared the results with an ARIMA model and WT-ARMA model, revealing that the

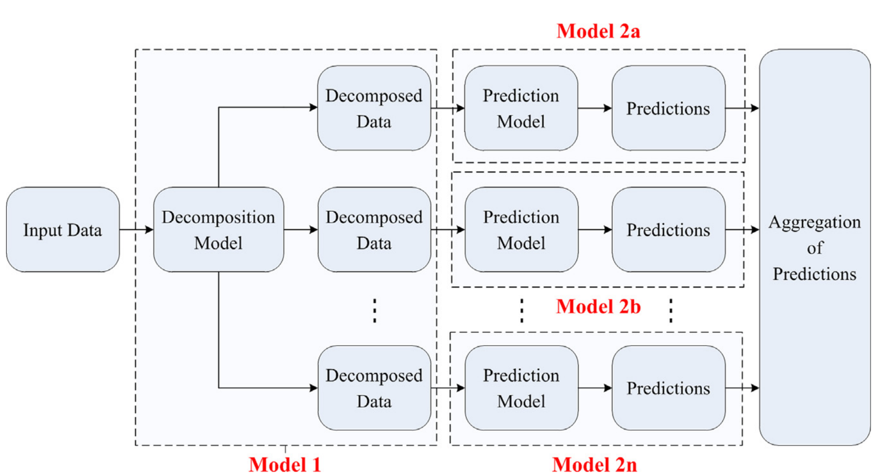

Fig. 2. Flowchart of combined approaches including data pre-processing techniques.

transformation of time series data has the potential of improving prediction performance [56]. Again with a three-resolution level wavelet decomposition, a WT-ARMA approach was proposed for a prediction horizon of six hours. The best performing type of ARMA model was determined through the Root Mean Square Error (RMSE) values and an improvement of the forecast results was accomplished after the pre-filtering of the data compared to persistence model [57]. Lastly, another WT-ARMA method was proposed by Ling et al. and the results confirmed the importance of data pre-processing in wind forecasting [58].

Recently, it is appealing to apply the WT method together with the machine learning approaches due to the well-known effectiveness of these approaches in wind forecasting. Wei et al. and Zhang et al. established similar forecasting models composed of a BPNN and a WT method with improved results [59,60]. As an alternative approach, Bhaskar and Singh put forward a novel wind power forecasting method for a prediction time of 30-h-ahead [61]. The main structure of the forecasting method was based on a combination of an Adaptive Wavelet (AW) NN model and a FFNN model. After the decomposition of the wind data by WT technique, AWNN model, which is a class of FFNN with activation functions based on wavelet basis functions, performed the forecasting processes for each decomposed signal. The one-year period of evaluation showed that the developed model has lower forecasting errors compared with the widely preferred benchmark methods. Lastly, the WT method in combination with a FFNN model was implemented by the authors for short term wind power predictions with the objective of providing an efficient operation in a stand-alone hybrid system [62]. In the mentioned study, it was aimed to increase the prediction accuracy while excluding the highest frequency band obtained from the wavelet decomposition in the reconstruction process of the future predictions due to the fact that these frequencies represent the stochastically fluctuating wind speeds which generally cause higher prediction errors.

Another machine learning algorithm, the SVR method, was also equipped with wavelet decomposition by Chen et al. and firstly different frequency components were obtained in the same way as those in other WT-based methods [63]. After reconstructing phase space of each component, the SVR method was applied to the components, following by the combination of the forecasted results of each frequency bounds. The comparisons carried out for different horizons and test data proved the positive effect of utilizing a data decomposition method in wind forecasting. A similar forecasting procedure was pursued by Liu et al. without using the theory of phase space reconstruction and the forecasting error measures were compared with a RBF–SVM method developed, indicating the better performance of the WT-SVM model [64]. Besides, a first-order and one-variable grey model (GM(1,1)) combined with a cloud model was utilized for wind power forecasting together with a wavelet decomposition [65]. Herein, low and high frequency parts of the decomposed wind signal were estimated by GM(1,1) and cloud model, respectively. Then, the fusing of the estimated signals led to an improvement compared to the single GM(1,1) model in terms of the accuracy of three-hours-ahead power predictions. To sum up, it can be concluded that the WT method can generally facilitate the prediction process and improve the performance; however, the decision of the selection of the decomposition level must be carefully made. In this subject, it can be indicated that lower decomposition levels mostly lead to better results.

The EMD method, introduced by Huang et al. [66] for the decomposition of non-stationary signals into a series of oscillatory functions, namely, Intrinsic Mode Functions (IMFs), has also been recently utilized for the purpose of wind data processing especially due to the fact that the method is not constrained by the difficulties in parameter selection such as the selection of the order or type of mother wavelet in WT decomposition [53]. Xiaolan and Hui proposed the EMD method in order to decompose the wind speed series into a number of better-behaved subseries prior to the forecasting process with different LSSVM models for one-month-ahead power forecast [67]. Besides, Guo et al. integrated the EMD method with FFNN model and it was noted that the accuracy of the predictions of each subseries obtained as well as of original series was considerably improved [68]. The decomposed wind speed and power series can be estimated with different approaches in order to increase the prediction performance and subsequently, the components can be aggregated to obtain the final forecast. In Ref. [69], the residual component derived from the EMD model was predicted with a grey forecasting model and the IMF components were predicted with either the largest Lyapunov exponent method or grey forecasting model according to the characteristic of the IMF component. Besides, Dejun et al. built up a model which utilizes both WT and EMD decomposition methods before a wind speed forecasting process [70]. In this study, the highest frequency band obtained from the EMD decomposition, called as IMF(1), was re-decomposed by the WT method because of a similar reason denoted in Ref. [62]. Then, each frequency band was forecasted with a different LSSVM model, leading to less Mean Absolute Percentage Error (MAPE) and RMSE values compared to single LSSVM model.

The wind data used in the training process of the forecasting models is of significant importance in terms of accuracy of forecasting model and computational time. In the literature, prediction accuracy is often reported as proportional to the amount of input data and computational time. However, it can be possible to increase prediction accuracy while utilizing only a subset of the data, following by a reduction in required time of prediction process. In this sense, grouping the wind data according to the similarities between the data sets and filtering the similar groups in order to determine the most relevant input parameters is a widely preferred method for this objective. This data pre-processing method, the so-called clustering method was utilized for power prediction by Kusiak and Li with various data-mining algorithms such as the Random Forest Algorithm (RFA), Boosting Tree Algorithm (BTA), SVM, NN, and a NN Ensemble [71], by Zhou et al. with ARMA model [72] and by Wang et al. with BPNN model [73]. All the three studies indicated that the clustering approach is capable of improving the forecasting skill using less input parameters and simulation time.

The other combined studies including a data pre-processing approach can be summarized as follows: Xingjie et al. utilized chaos analysis before an Elman network in order to increase the accuracy of the 12-step-ahead wind speed predictions [74]. Due to its advantages of selecting the influential inputs automatically, Abdel-Aal et al. implemented an abductive network for mean hourly wind speed predictions [75]. Furthermore, Markov chain (MC) approach was made use of in conjunction with MLP model in Ref. [76] for similar purposes. Then, Shuang et al. dealt with rough set algorithm to determine the main affecting factors of power prediction among the various meteorological conditions and subsequently, an ANN model was put forward for wind power predictions while using these factors as additional inputs [77]. Afterwards, Wu et al. eliminated the incorrect data caused by several reasons such as erroneous measurement and switching operations of wind turbine thanks to Grubbs Test and carried out one-hour-ahead predictions with a RBFNN model [78]. In order to select the most related variables with wind speed and hence improve the prediction performance, Haque et al. proposed the Similar Days (SD) method and subsequently, the soft computing models, namely, BPNN, RBFNN and ANFIS, were applied to the selected data [79]. Moreover, a Principal Components Analysis (PCA) was integrated with an ANN model for a similar variable reduction purpose in Ref. [80]. A V-system method, which is similar to WT and EMD methods in terms of its main function, was

introduced for decomposing the wind speed time series into a number of components in different frequencies and LSSVM models were utilized for prediction of each frequency band before a reconstruction process with inverse V-system transform [81]. In [82], Kalman filter was employed to modify the wind speed data generated from the WRF model and the resulting wind speed values as well as the predictions of other meteorological condition from the WRF model were fed into an ANN model to forecast the wind power. Lastly, Liu et al. described the probabilistic NN to remove the invalid data recorded and a complex-valued recurrent NN was used to predict wind power [83]. In conclusion, it can be observed that usually better results are obtained with data pre-processing methods, meaning that data decomposition and filtering of ineffective data appreciably contribute to the performance of wind speed forecasting approaches.

3.2.2. Combined approaches including parameter selection and optimization techniques

In a large numbers of papers on wind forecasting, it has been reported that certain parameter selection and optimization approaches also can make a considerable contribution to the prediction performance during the training process. The selection of explanatory variables and determination of model parameters while using the mentioned approaches can allow avoiding the time consuming process of the optimization of the prediction method, which is usually carried out by testing the method over a large number of candidate parameters and deriving the structure of the model heuristically. The approaches in question perform the predictions after a parameter evaluation process with a suitable method, as shown in Fig. 3.

Among the mentioned cascade structures, a major part of the studies in the literature has concentrated on Genetic Algorithms (GAs) due to its capability of fast convergence to global optima and relatively simple implementation. In this concept, Xingpei et al. dealt with a BPNN model in which the initial weights and bias are optimized by employing a GA model [84]. The results of the prediction showed that convergence rate and prediction precision of the GA–BP model is superior compared to two different BPNN models. A similar structure was built by Kolhe et al. and the employed GANN model was tested with real values, leading to an improvement on forecast accuracy except for the wind gust speeds [85]. Furthermore, GA was combined with grey NN for similar purposes in Ref. [86] and in a comparative study, Flores et al. applied GA algorithm so as to estimate ARMA coefficients and ANN weights after determining the variables to be utilized in the models [87]. Lastly, SVM-based models were integrated with GA approach in order to improve the prediction performance. To this end, GA models were used for selecting the optimal parameters of a local SVR model in [88] and of LSSVM models in [89,90].

Other evolutionary algorithms apart from GA algorithm such as Evolutionary Programming (EP) and Differential Evolution (DE) are also popular methods for parameter optimization-based techniques. Salcedo-Sanz et al. dealt with the application of the mentioned two

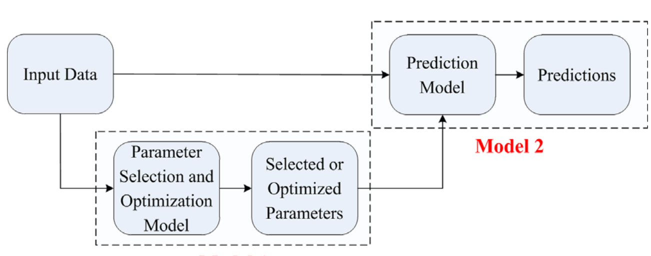

Fig. 3. Flowchart of combined approaches including parameter selection and optimization techniques.

evolutionary-based approaches, EP and PSO, for parameters tuning of SVM within the framework of wind speed prediction and compared the performances of the approaches at a real wind farm in Spain [91]. Moreover, a Ridgelet Neural Network (RNN), which is a kind of NN that employs ridgelet as the activation function in a FFNN, was used for wind speed and power predictions [92]. In this study, a new DE algorithm was opted to train the RNN due to its high capabilities of avoiding local optima and good convergence speed. Besides, the weights of a first order Takagi–Sugeno FIS model were determined using an evolutionary PSO algorithm under Renyi's Entropy-based criterion in Ref. [93] and the weights as well as the structure of a Hyperbolic Tangent Unit (HTU) NN were selected with a hybrid evolutionary programming in Ref. [94].

The algorithms based on Kalman filter, which is an effective recursive algorithm for estimating the states of the system by minimizing the MSE values, have also been proven effective for combined wind speed and power forecasting approaches. Li put forward a Recurrent MLP (RMLP) network model for one-step power production, which was trained by an Extended Kalman filter (EKF)-based BP through time algorithm [95]. Similarly, the EKF method was used with the aim of training for a High Order NN (HONN) model by Alanis et al. and hourly wind speed predictions were performed with reasonable results [96]. Afterwards, the same author employed the EKF method as well as the PSO method for the training process of a RMLP model, while obtaining an EKF–PSO parameter optimization technique and wind speeds were estimated on the basis of minute samples [97].

The other combined studies including a parameter selection or optimization technique are mentioned briefly as follows: Lei et al. and Wang et al. examined the rate of improvement in wind forecasting with the employment of chaotic time series in order to design an ANN model [98] and a SVR model [99], respectively and the results validated the effectiveness of the approach. Furthermore, Chen et al. proposed the Orthogonal Least-Squares (OLS) method instead of a gradient search technique for selecting the number of the centers in the hidden layer of a RBF network [100] and then, the authors included Culture Algorithm (CA) to the mentioned OLS–RBF combined model for tuning the parameters in the network [101]. Thus, it was concluded that OLS and CA methods can assist in improving the prediction performance. Besides, the Simulated Annealing (SA) method, which is a well-known optimization method, was proposed for selecting the parameters of a SVM model [102]. In a more recent study, Han et al. developed a BPNN model in which the connection weights are optimized using Memory Tabu Search (MTS) algorithm for the purpose of increasing prediction accuracy and convergence rate [103]. With the same objective, an approach called as Imperialist Competitive Algorithm (ICA) was introduced in Ref. [104] in order to optimize the weights of MLPNN. Herein, the forecasts were realized for 36-h-ahead at one-hour intervals by using forecasted meteorological conditions from NWP and measure data from SCADA system as inputs. Also, the potential of the Gauss–Markov theory was investigated so as to calculate the parameters of a Kalman filter model for short term predictions and an increment in the prediction accuracy was obtained compared to the persistence method [105].

All the mentioned studies come to a similar conclusion that suitable parameters can considerably affect the model accuracies. In addition, a few studies in the literature have utilized both data pre-processing and parameter selection techniques in order to enhance the forecasting performance. For instance, the study on one-hour-ahead wind power prediction by Jursa and Rohrig falls into this class. In this study, the authors constructed a PSO–DE model for the purpose of choosing the most appropriate input variables and model parameters such as numbers of hidden neurons for two prediction models, namely, ANN and the nearest neighbor search [106]. Hence, the mentioned optimization methods refined the candidate inputs and a reasonable increase in performance was obtained compared to

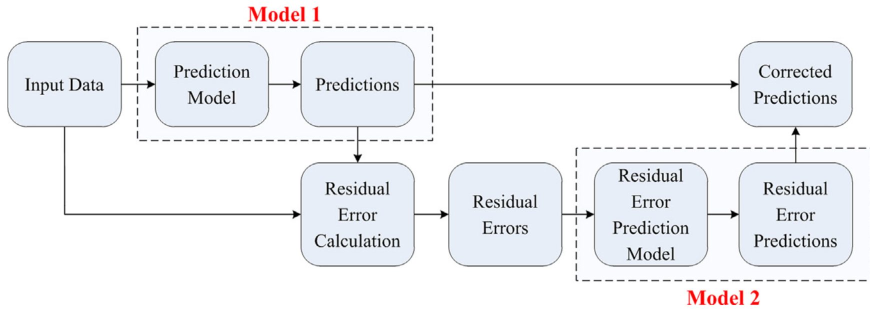

Fig. 4. Flowchart of combined approaches including error processing techniques.

the results of ANN with the manually selected variables. Also, in order to improve the forecasting accuracy, Zhang et al. utilized the SEA method first to cut up the daily mean wind speed data into seasonal and trend components and then to filter out the seasonal component [107]. Subsequently, the PSO method was applied to determine an important parameter in the main forecasting model which is a First-Order or Second-Order Adaptive Coefficient (FAC and SAC) method. It was concluded that both parameter selection and data decomposition methods are very effective techniques in accurate wind speed predictions. Besides, an ANN-based prediction model was developed by Guo et al. while employing the rough set theory for reduction of input parameters and GA for optimizing the initial weights of NN [108].

3.2.3. Combined approaches including error processing techniques

Apart from the approaches mentioned in Sections 3.2.1 and 3.2.2, there exists a few combined approaches in the literature that have a structure that takes into account the residual error values obtained from a forecasting model, as denoted in Fig. 4.

The importance of this technique lies in the fact that the negative effects of the systematic errors, which imply that the predicted values are over- or underestimated in most of the time and are likely to encounter in all prediction models, on the prediction accuracy can be diminished to a certain extent. Incorporation of the residual error values to the predicted series mostly leads the precision of the predictions to further increase. In this concept, Louka et al. employed the Kalman filtering technique to reduce the systematic errors of two NWP models, namely, SKIRON and RAMS models [109]. Subsequently, the power predictions were performed with an adaptive Fuzzy-NN (F-NN) model using the filtered wind speed predictions as input and a strong improvement in the forecasting skill as well as in required CPU time was reported for different forecasting periods compared to the same model using unfiltered predictions. With a similar purpose, GM (1,1) model was used in conjunction with Markov model by Chen [110]. In this study, it was aimed to increase prediction accuracy by first predicting wind speed with GM (1,1) model and then correcting the predicted values with the latter model. The correction process followed can be explained in three steps: (1) calculating the residual error by subtracting the predicted wind speed values from the observed values, (2) dividing the error values derived into different states with Markov model, and (3) estimating the error values by calculating the probability distribution of each state. Finally, the wind speed predictions were transformed into power predictions through a power curve, as usual in the literature and a higher accuracy was obtained compared to GM (1,1) model. In a more recent study, wind speed time series was predicted by an ARIMA model and the residual errors obtained were simulated by a GARCH (1,1) model, which has several advantages over ARCH model such as less parameter number and thereby less computation burden [111]. Hence, it was shown that the output of the proposed combined approach more closely approximates the measured wind speed than that of a single ARIMA model.

4. Discussion and prospects

In the literature, there exist a lot of studies on the predictions of wind speed and power with various methods, which mostly generate reasonable values and each method has its own advantages and disadvantages. However, due to the fact that the prediction models developed are generally site-specific and considerably influenced by the changing of required prediction times, the suitable model is selected regarding the specific data characteristic of the site and the application area of the method with a time-consuming and specialist process. In order to address this problem by avoiding the ambiguity of model selection and to further improve the prediction performance, combining several methods have been proposed, especially at the last years and the results obtained have verified the effectiveness of these approaches. The subject of combined wind speed and power forecasting methods can be deemed as a novel research area. Therefore, a consensus has not yet been reached concerning the fundamentals of the subject and the basic definitions about the related terms. For instance, it can be readily indicated that predictions errors are always proportional to the prediction time; however, it is not possible to say exactly which method is the most appropriate candidate for a certain prediction time. In this issue, only some suggestions and assumptions are available at this stage. Likewise, the classification of the methods according to the prediction time is another subject that is suggested in various ways in the literature. For instance, the short term prediction is defined as the predictions up to six-hour-ahead in Ref. [79]; however, it corresponds to 24-h-ahead predictions in Ref. [112] and 72-h-ahead predictions in Ref. [7]. Besides, comparison of the forecasting performance of the models is another troublesome topic evidently due to the fact that no single model provides the best predictions in terms of all performance metrics, meaning that a universal standard for a fair comparison of prediction performances is not yet present.

Similar to the above mentioned problems, it is important to highlight that there still exist discrepancies in the definitions and structures of the combined and hybrid forecasting approaches and this situation complicates the classification and comparison of the approaches. For this purpose, the approaches were divided into several main and sub-categories and the effects of different models on the forecasting performance are briefly described and discussed by pursuing an extensive body of the literature in this direction. According to the mentioned studies, firstly there is no doubt that combination of proper prediction techniques is of significant importance in terms of improving the accuracy. Then, the preliminary processing of the input data, particularly with WT and EMD methods, has been found valuable for facilitating the forecasting process and thereby, improving the prediction quality

Table 2
Brief evaluation of combined approaches applied for forecasting of wind speed and power in the literature.

Combined wind speed/ power forecasting approach	Strategy	Advantages	Disadvantages	Literature studies
Weighting-based combined approaches	Assigning weight factors to models according to their performance	Easy to implement and code, suitable for a wide range of prediction time, adaptive to new data	Does not guarantee the best predictions along the prediction horizon, requires an extra model for determining the weights	[41–53]
Combined approaches including data pre-processing techniques	Forecasting of the subseries obtained by decomposition models	Higher performance compared to other approaches, easy to find literature examples, robustness to rapid changes in wind speed	Requires a detailed mathematical knowledge on decomposition models, provides slow response to new data	[54–83]
Combined approaches including parameter selection and optimization techniques	Optimization of the parameters of forecasting model	Easy to find literature examples, a relatively basic structure	Harder to code, dependent on designer's knowledge about the optimization problems, computationally intensive	[84–108]
Combined approaches including error processing techniques	Forecasting of residual error caused by forecasting model	High accuracy, effective in reducing systematic error	Computational time inefficiency	[109–111]

with the cost of spending more time on final model building. Likewise, it was observed that evolutionary algorithms such as GA, EP and DE methods and Kalman filtering method tend to perform well for the selection and optimization of the prediction system parameters. Moreover, it was realized that the total performance of the prediction methods can be augmented by also predicting and then including the residual error values with a variety of models. A brief evaluation about each class of the combined approaches which is determined according to the above mentioned criterion is shown in Table 2.

By examining the characteristics of the combined approaches summarized in Table 2, it can be concluded that the approaches with a weighting model and with a data pre-processing model are very suitable for longer and harder prediction tasks, which are required for power system operations such as scheduling, unit commitment and load following. Weighting-based approaches consisting of an NWP model should also be utilized effectively for the much longer term objectives such as maintenance of wind turbines or conventional power plants. Besides, the approaches including parameter selection and data optimization techniques may present high-accuracy predictions required mainly for energy trading and marketing. However, the approaches with an error processing method may only give reasonable results in the case of systematic errors and hence are not of a specific application area. Lastly, it is worth mentioning that the combined models are ineffective in very short term forecasts, ranging from milliseconds up to a few minutes and used for wind turbine active control, due to the fact that these approaches have generally computational time inefficiency compared to the individual methods.

5. Conclusions

The continuing increase in wind energy penetration in the last decades has necessitated more accurate as well as more rapid wind power predictions. Also, the new power delivery concepts such as smart grids and Virtual Power Plants (VPPs) have increased the value of accurate predictions. Therefore, recent researches have been oriented to develop new approaches and among the mentioned studies, combining different methods has gained more popularity due to the fact that single methods cannot mostly guarantee accurate predictions, particularly for longer prediction times and various sites such as offshore and complex terrain. Herein, the critical issues are how to combine single models and to cluster the combined models into several meaningful groups. Motivated by this need, in this paper, first a detailed review on the wind speed and power methods is presented and then emphasis is given to the combination of the models. To this end, the combination models are classified and briefly explained together with a large number of studies from the literature. In conclusion, it is put into evidence that combined approaches generally outperform the single models and based on the results of the comparisons presented in the literature, the possible trend in combining models is proposed.

Another important result of the study is that the performance level of a combined model varies mainly depending on two factors: the main objective of the prediction and the characteristic of the available wind data. For instance, the combined approaches including data pre-processing techniques should be a good candidate for a long prediction horizon and complex wind data. On the contrary, these approaches should be avoided for the applications requiring a fast response due to their slow adaptation to new data. Accordingly, the development or modification of a decomposition method which meets the desired operation times in relatively fast applications should make a considerable contribution to the forecasting literature. Similarly, the weighting-based approaches have a long total response time whereas they are inherently adaptive to the time-varying data sets. In this class of approaches, the prediction accuracy and speed should be increased significantly with an effective weight assignment method, which has recently emerged as a hot research topic in the area of combined forecasting models.

The combined models can also be utilized for the purpose of solar radiation and temperature predictions, with minor modifications, followed by the calculation of the solar power predictions. The existing studies on utilizing combined models for solar power forecasting are very limited. Thus, more studies are required to advance the present knowledge. Finally, it is important to mention that the combined approaches composed of several spatial correlation models, which deal with the correlation of wind speed in the neighboring sites instead of in time domain, have not been included in this study owing to the fact that this topic is beyond the scope of this paper. The evaluation and comparison of these models should be considered as a future study because of their successful implementations.

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